fMRI Deconvolution via Temporal Regularization using a LASSO model and the LARS algorithm

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***Abstract*— In this work we propose a novel approach to deconvolve the blood oxygenated level dependent (BOLD) signal to recover underlying neurons activations and their dynamics.**

I. INTRODUCTION

Deconvolution methods are used to denoise the blood oxygen level-dependent (BOLD) response, the signal that forms the basis of functional MRI (fMRI) [1]. In this work we propose a temporal regularized deconvolution of BOLD fMRI signal with the least absolute shrinkage and selection operator (LASSO) model, solved using the Least-Angle Regression (LARS) algorithm.

II. METHODS

We implemented the deconvolution exploiting the sparsity of the innovation signal s(t) [2], and we built a LASSO model:

$$s^* = \underset{s}{\operatorname{argmin}} \left\{ \frac{1}{2n} \left\| y - HI_\alpha s \right\|_2^2 + \lambda \|s\|_1 \right\}$$

where n is the signal length, H represents the hemodynamic response function [3] and λ is the regularization parameter. I_α is the exponential accumulation function given by:

$$I_\alpha(z) = S \left[\frac{e^{-\alpha} z^{-1}}{(1 - e^{-\alpha} z^{-1})^2} - \frac{e^{-\alpha} z}{(1 - e^{-\alpha} z)^2} \right] \frac{1}{(1 - z^{-1})^2}$$

such that the activity-inducing signal $u(t) = I_\alpha * s(t)$, normalized by the factor S. We chose $\alpha = 0.75$ experimentally within the range [0, 3]. We minimized the objective function using LARS [4], that outputs all λs of interest and their associated solutions. We used the L-curve to estimate the λ^* corresponding to the optimal solution s^*. Then, as in [2], we scaled a 3D activation map computed with FSL in the range [0, 3], with a 2-mm isotropic resolution (Fig.1b). We multiplied it by two block-type signals of 200s, u(t): A) with 4 onsets, and B) with one long onset. We corrupted the signals with model and block-type noise, we convolved them with H and we added Gaussian noise thus simulating the fMRI time series y(t). We solved the inverse problem and we recovered $u^*(t) = I_\alpha * s^*(t)$ as described above. Finally, to evaluate the results, we computed the root of the mean square errors (MSE) and standard deviation (STD) between u(t) and $u^*(t)$ averaged among the voxels belonging to the grey matter masked activation. We compared our results with those obtained with the temporal regularization implemented in the Total Activation (TA) toolbox [1]. We tested the above procedure on the preprocessed task-fMRI image of one subject taken from the Human Connectome Project (HCP) database [5]. The reconstructed $u^*(t)$ were averaged in a ROI of 6 × 6 × 6 mm^3 centered in the Brodmann Area 4p (MNI coordinates: 62, -14, 30).

III. RESULTS

Table I shows that the MSEs±STDs change for different peak-SNRs (pSNRs) and that they are lower than the ones obtained using the TA toolbox. Fig.1.a and c show examples of the reconstructed activity inducing signal using our approach (u^*) and the approach in [1] (u^*_{TA}).

TABLE I. SUMMARY OF ROOTED *MSES AND STDS*

Activation		**A**			**B**		
pSNR [dB]		5.17	4	3.98	7.64	5.94	5.12
OUR $\alpha = 0.75$	*RMSE*	**0.11**	0.22	0.18	**0.05**	0.19	**0.14**
	STD	**0.13**	0.16	0.14	**0.05**	0.11	**0.08**
TA	*RMSE*	0.24	0.29	0.3	0.19	0.24	0.25
	STD	0.31	0.32	0.33	0.23	0.24	0.26

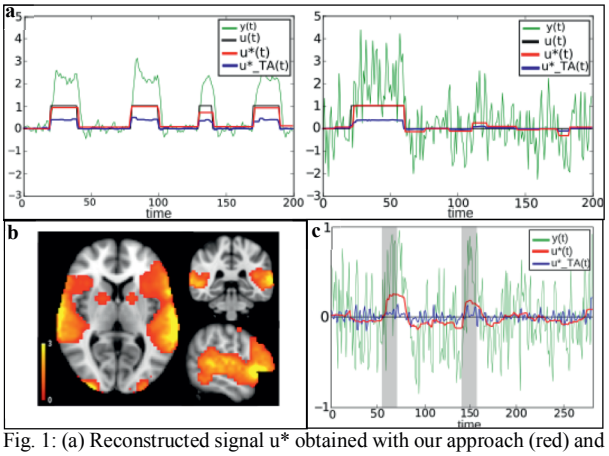

Fig. 1: (a) Reconstructed signal u* obtained with our approach (red) and the TA (blue) superimposed on the activation (black) and fMRI signal (green). The plots are related to different activations and pSNRs: activation A, pSNR = 5.17 dB (left); activation B, pSNR = 5.12 dB (right). (b) Activation map. (c) Results of HCP data. Same legend of panel (a); the grey areas represent the duration of the tongue movements.

IV. DISCUSSION & CONCLUSION

Our findings show that the joint use of LARS and the L-curve for solving our optimization problem allowed us to choose the optimal λ^* and related solution among all those outputted by the algorithm. Thus, we decreased the computation time and avoided a need of defining λs a priori, allowing to improve brain dynamics recovery in future clinical application.

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